

Towards automatic exploration of bifurcation diagrams for large-scale applications

Parallelizing Python code on a budget

Jonas Thies^{*}, Rebekka-Sarah Hennig^{*} and Michiel Wouters[†]

^{*} Institute of Simulation and Software Technology
German Aerospace Center (DLR)

[†] University of Antwerp, Belgium



project ESSEX

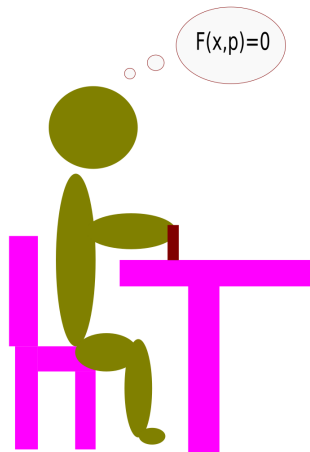


Knowledge for Tomorrow



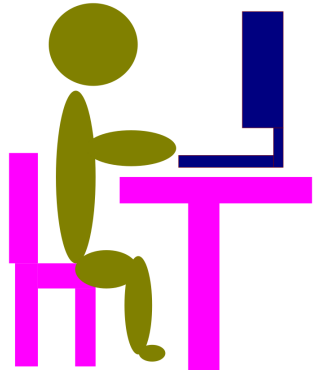
Motivation

- develop method on paper



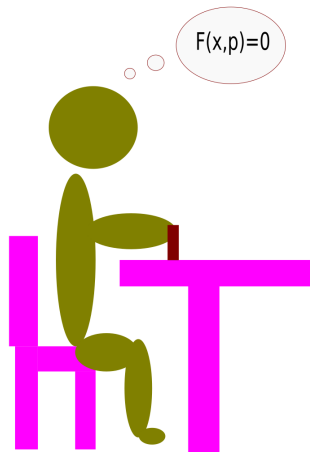
Motivation

- develop method on paper
- implement for numerical evidence



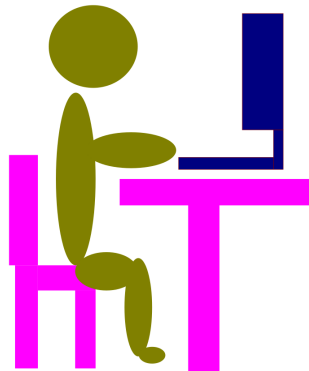
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence



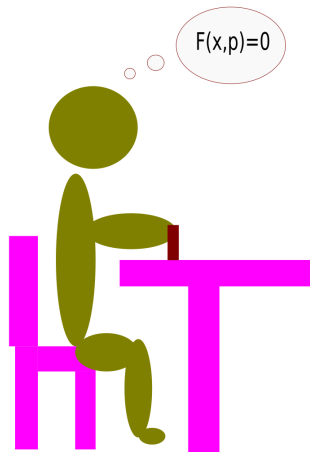
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence



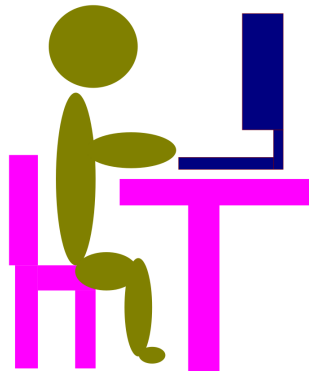
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence



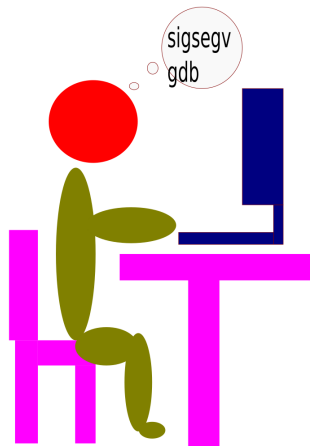
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence



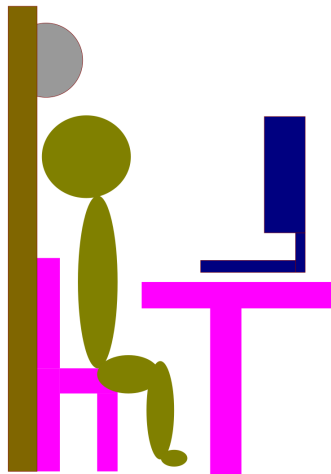
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence
- can be frustrating...



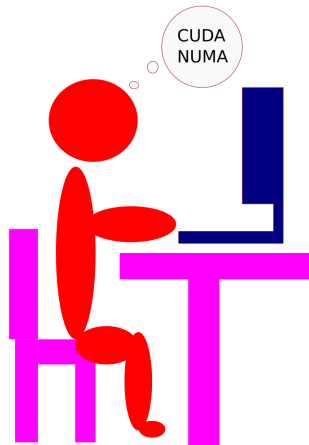
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence
- can be frustrating...
- 3 months before the end of your defense, your supervisor asks you to demonstrate scalability on a heterogenous supercomputer.



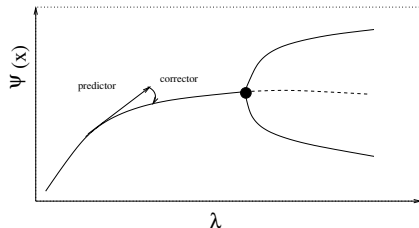
Motivation

- develop method on paper
- implement for numerical evidence
- iterate until convergence
- can be frustrating...
- 3 months before the end of your defense, your supervisor asks you to demonstrate scalability on a heterogenous supercomputer.



Introduction

- We seek steady states of some discretized PDE
- \Rightarrow nonlinear system
 $F(x, \lambda) = 0, F : \mathbb{R}^N \rightarrow \mathbb{R}^N$
- Jacobian $J(x, \lambda) = \frac{\partial F_i(x, \lambda)}{\partial x_j}$
 - large
 - sparse
 - non-Hermitian
 - possibly singular



Numerical methods:

1. Newton-Raphson
2. Krylov (GMRES)
3. preconditioning
4. bordering/deflation
5. sparse eigensolver (e.g. JDQR)



Existing Software: LOCA



LOCA

Library Of Contin-
uation Algorithms

(+)

(-)

- parallel linear algebra from Epetra/Tpetra
- algorithmic building blocks from Trilinos (NOX, Belos, ...)
- pseudo-arclength continuation ('stepper')
- basic techniques for bifurcation detection and branch switching

- requires good C++ skills
- no automatic exploration techniques

⇒ significant human effort

<https://trilinos.org/>



Existing Software: PyNCT

PyNCT

Python Numerical
Continuation Toolkit

(+)

- written in Python
- advanced algorithms, focus on robustness
- handle symmetries
- automatic exploration

(-)

- restricted to NumPy/SciPy
- limited problem size
- re-invention of the wheel (GMRES etc.)
- no unit tests



Another sparse solver library: PHIST

PHIST Pipelined, Hybrid-parallel
Iterative Solver Toolkit

interfaces: C, C++, Fortran, Python

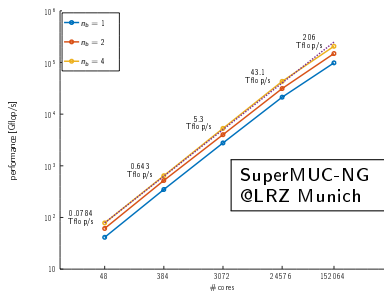
eigensolver: Jacobi-Davidson QR

interoperability and portability:

- extensive testing and benchmarking capabilities
- select backend at compile time:

GHOLST, builtin (F'03), **TRILINOS**, PETSc

Extrme-scale performance



<https://xsdk-info.org/>

<https://bitbucket.org/essex/phist/>

Block Jacobi-Davidson QR

- Aim: partial QR decomposition, $AQ = QR$, $R \in \mathbb{C}^{k \times k}$ upper triangular,
- $\frac{1}{2}Q^T Q - \frac{1}{2}I = 0$, $Q \in \mathbb{R}^{N \times k}$.

Newton's method, let $Q = \tilde{Q} + \Delta Q$

- $A\Delta Q - \Delta Q\tilde{R} = A\tilde{Q} - \tilde{Q}\tilde{R}$
- $\tilde{Q}^T \Delta Q = 0$



Block Jacobi-Davidson QR (2)

This leads to a set of *correction equations*

$$(I - \tilde{Q}\tilde{Q}^T)A(I - \tilde{Q}\tilde{Q}^T)\Delta Q - \Delta Q\tilde{R} = A\tilde{Q} - \tilde{Q}\tilde{R}$$

- Subspace acceleration: add corrections to expanding search space V
- Ritz-Galerkin: $M = V^T A V$, $M = S^H R S$
- Lock converged eigenpairs \Rightarrow growing projection space \tilde{Q}
- Solve correction eq. using (deflated) GMRES or MINRES Krylov solver
- Restart with $m_{min} > n_{eigs}$ vectors when basis becomes too large



Exploiting the PHIST interface

Example PHIST function (in C): $W \leftarrow V \cdot C$

```
void phist_Dmvec_times_sdMat(double alpha, Dconst_mvec_ptr V,  
    Dconst_sdMat_ptr C, double beta, Dmvec_ptr W, int* iflag);
```

using the auto-generated Python function:

```
from phist_kernels import *  
V=Dmvec_ptr()  
PYST_CHK_IERR(Dmvec_create,V,map,ncols)  
[...]  
PYST_CHK_IERR(Dmvec_times_sdMat,-2,V,C, 1,W)  
[...]  
PYST_CHK_IERR(Dmvec_delete,V)
```



Exploiting the PHIST interface (2)

More user-friendly:

- `linalg` module with objects like `mvec` (multi-vector)
- store pointer to underlying PHIST object
- small objects (`sdMats`) stay NumPy

Note: we deliberately don't overload operators to stay in control

- which kernels are used
- when data is copied or 'viewed'

An **mvec cache** is used to avoid creating/deleting temporary vectors all the time



PyNCT with transparent linalg objects

Example: MGS orthogonalization in GMRES

original:

```
for j in range(it+1):  
    alpha=ip(V[:,j],w)  
    H[j,it]+=alpha  
    w=w-alpha*V[:,j]
```

with linalg:

```
for j in range(it+1):  
    alpha=ip(V.view(0,n,j,j+1),w)  
    H[j,it]+=alpha  
    Vj=V.view(0,n,j,j+1)  
    w.axpby(-alpha,Vj,1)
```



Example: a Turing system

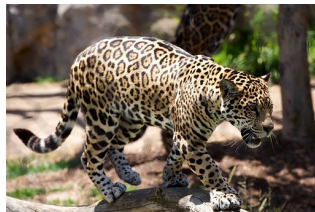
Barrio-Varea-Aragon-Maini (BVAM) model:

$$\begin{aligned}\frac{\partial u}{\partial t} &= D\delta\nabla^2 u + \alpha u(1 - r_1 v^2) + v(1 - r_2 u), \\ \frac{\partial v}{\partial t} &= \delta\nabla^2 v + v(\beta + \alpha r_1 uv) + u(\gamma + r_2 v),\end{aligned}$$

- on $\Omega = [0, 1] \times [0, 1]$,
- periodic boundary conditions.

\Rightarrow lots of symmetry, especially in 3D

Preconditioning by standard AMG



Example: a Turing system

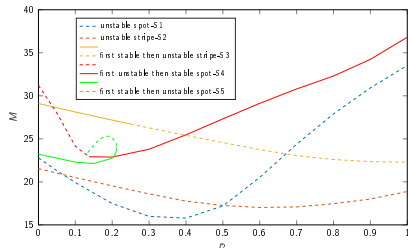
Barrio-Varea-Aragon-Maini (BVAM) model:

$$\begin{aligned}\frac{\partial u}{\partial t} &= D\delta\nabla^2 u + \alpha u(1 - r_1 v^2) + v(1 - r_2 u), \\ \frac{\partial v}{\partial t} &= \delta\nabla^2 v + v(\beta + \alpha r_1 uv) + u(\gamma + r_2 v),\end{aligned}$$

- on $\Omega = [0, 1] \times [0, 1]$,
- periodic boundary conditions.

⇒ lots of symmetry, especially in 3D

Preconditioning by standard AMG

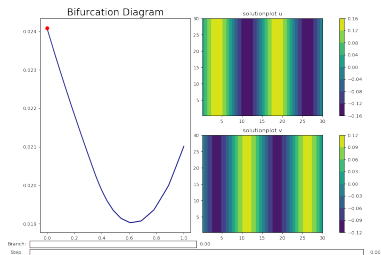


Typical bifurcation diagram

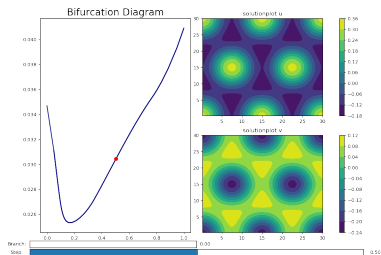
Song, Wubs, Thies & Baars: *Numerical Bifurcation Analysis of a 3D Turing-type Reaction-Diffusion Model*. CNSNS 2018



Results for Turing system



Branch 2, $n_x = 128$, solution at $r_2 = 0.0$



Branch 4, $n_x = 128$, solution at $r_2 = 0.5$



Comparison: PyNCT/Epetra \iff LOCA/Epetra

- Experiment: follow branch 4 for $r_2 = 0 \dots 1$
- 10 continuation steps
- compare operation counts, run time, scalability...

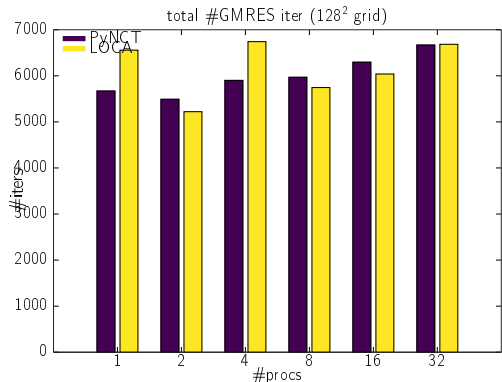
Caveat: algorithmic details are significantly different



Comparison: PyNCT/Epetra \longleftrightarrow LOCA/Epetra

- Experiment: follow branch 4 for $r_2 = 0 \dots 1$
- 10 continuation steps
- compare operation counts, run time, scalability...

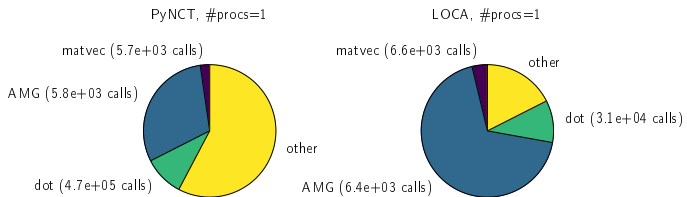
Caveat: algorithmic details are significantly different



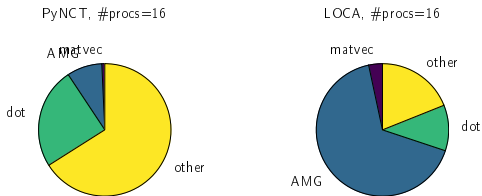
First observation: total number of GMRES iterations is similar



Performance - profiling (128² case)



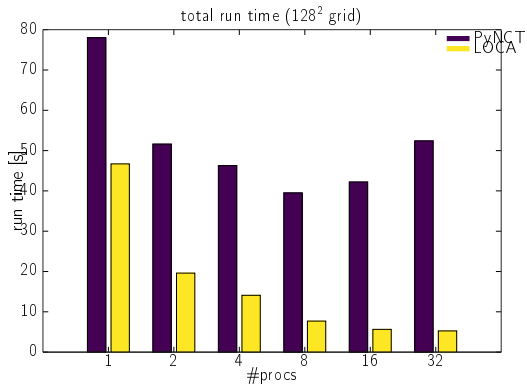
Performance - profiling (128² case)



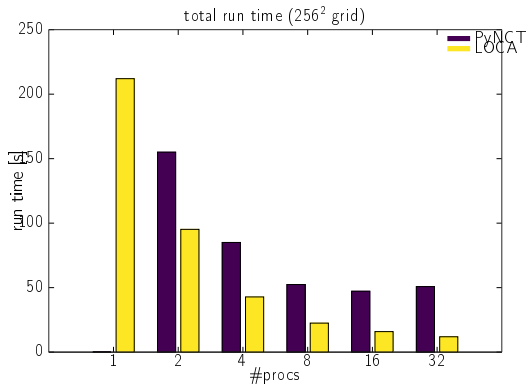
Observation: dot products and Python overhead bad for strong scaling



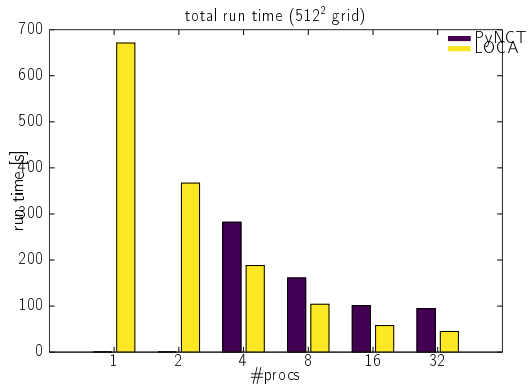
Overall performance comparison



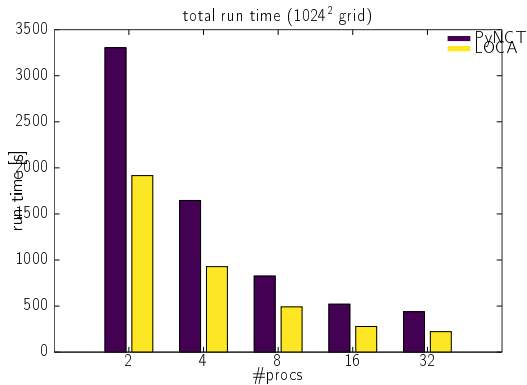
Overall performance comparison



Overall performance comparison



Overall performance comparison



Conclusion and outlook

Achievements so far

- working 'proof of concept'
- independent of 'backend'
- reasonably comfortable Python programming
- shared and distributed memory parallelism
- performance as expected

Improvements/future work

- call larger algorithmic building blocks from PHIST (GMRES, orthog, JDQR) to reduce overhead
- automatic exploration for non-Hermitian problems not working yet
- handle symmetry in 3D
- run 3D superconductor application

